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Research on Modulation recognition technology based on Machine learning

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Abstract: This paper presents a method for modulation recognition of digital signals using machine learning. This method first extracted seven characteristic parameters according to the instantaneous parameters and high-order cumulant characteristics of the signal, then combined the decision tree classifier, neural network classifier and support vector machine classifier in machine learning with these characteristic parameters, and finally realized the modulation recognition of MASK, MFSK, MPSK and MQAM signals. This method not only has low computational complexity and more recognized signals, but also improves the recognition rate at low SNR.

Keywords: Machine learning; Modulation recognition; Decision tree; Neural network; Support vector machine.

1. INTRODUCTION

With the continuous innovation of communication technology, wireless communication network environment is becoming more and more complex. In the non-cooperative communication environment, modulation recognition technology can recognize and classify the modulation type of blind signal and play a key role in signal detection and demodulation. Modulation recognition technology is of great significance in both civilian and military fields. At present, there are two types of automatic modulation recognition technology: one is modulation recognition based on maximum likelihood theory; The other is modulation recognition based on statistical mode. The former requires many prior conditions and is not suitable for non-cooperative communication environment. The latter requires less prior conditions and can realize blind signal recognition, which is widely used in engineering practice. The principle of modulation recognition technology based on statistical mode is shown in figure 1, which mainly includes signal preprocessing, feature extraction and classifier recognition.

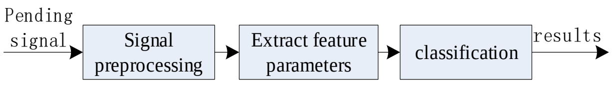

Figure 1. Modulation recognition based on statistical mode.

Signal preprocessing includes signal down conversion, carrier frequency estimation, bandwidth estimation, etc. Common methods for extracting feature parameters include instantaneous information[1], high-order cumulants[2], wavelet transform[3], spectral features[4], constellation map[5], etc. Common classification and recognition methods include decision tree[6], neural network[7], support vector machine[8], etc.

Modulation recognition based on statistical mode was first introduced in 1984. Liedtke proposed the concept of modulation recognition, and realized the recognition of digital modulation signals by using the parameters of signal amplitude histogram, frequency histogram, amplitude variance and frequency variance, etc [9]. With the development of machine learning, more and more people begin to use supervised learning to improve the efficiency of signal recognition. Recognition of digital modulation dignals using deep learning in document [10]; Cheol-Sun Park use support vector machine to improve the recognition effect [11]. Timothy J. O'Shea proposed using convolutional neural network to solve the problem of modulation recognition. Compared with the traditional classification algorithm in machine learning, it has been greatly improved [12].

In this paper, we use the machine learning classifier to realize the modulation recognition of signals. By analyzing the performance of different machine learning classifiers, we can provide guidance for engineering applications. At the same time, a new joint feature parameter is proposed, which can improve the accuracy of signal recognition.

The remainders of the paper are organized as follows: Section 2 discusses signal model and feature extraction of signal, which will provide a basis for using machine learning classifier. In Section 3, we will design the classifier and introduce the basic principles of the three classification algorithms. At Section 4, we introduce the experimental environment and carry out the experimental test, and analyze and compare the test results. Section 5 concludes the paper.

2. EXTRACTION FEATURE

The types of modulation signals to be identified in this paper are ASK, 4ASK, MSK, 2FSK, 4FSK, BPSK, QPSK, 8PSK, 16QAM and 64QAM. The unified mathematical expressions of these ten signals can be expressed as follows:

$$S(t) = a(t)\cos(w_c t + \phi(t)) \tag{1}$$

In the formula, w_c is the angular frequency of the signal, $\phi(t)$ is the phase of the signal, $a(t)$ is the amplitude of the signal.

2.1 Instantaneous feature parameters

In this paper, instantaneous information parameters are selected from non-weak signal segments, and the zero center and normalization of the parameters are processed. The instantaneous feature parameters extracted in this paper include the following contents:

(1)Logarithm of second-order origin moment of instantaneous amplitude:

$$Ma_1 = \lg\left[\frac{1}{N_s}\sum_{n=0}^{N_s-1} A_{cn}^{\ 2}(n)\right] \tag{2}$$

In the formula, N_s is all sampled data points, and A_{cn} is the instantaneous amplitude with zero center and normalization. The instantaneous amplitude can be used to represent the envelope change of the signal.

(2)Logarithm of the origin moment of the absolute value of instantaneous amplitude:

$$Ma_2 = \lg\left[\frac{1}{N_s}\sum_{n=0}^{N_s-1} |A_{sn}(n)|\right] \tag{3}$$

A_{sn} is the normalized instantaneous amplitude after recursion. This parameter can distinguish 2ASK signal from 4ASK signal.

(3)Second-order amplitude moment of MQAM signal:

$$M_{asm} = M_{2,MQAM}^{2n} = \frac{M-1}{3}a^2 \tag{4}$$

The theoretical values of 16QAM and 64QAM are 5 and 21 respectively, so the two signals can be clearly distinguished by this parameter.

(4)Logarithm of origin moment of absolute value of instantaneous frequency:

$$Mf_1 = \lg\left[\frac{1}{N_s}\sum_{n=0}^{N_s-1} |f_{cn}(n)|\right] \tag{5}$$

f_{cn} is the normalized instantaneous frequency of zero center. Through this parameter, MPSK signal and MFSK signal can be distinguished.

2.2 Characteristic parameters of higher-order cumulants

The theoretical values of five kinds of higher-order cumulants for each signal are given in Table 1. According to the theoretical values, the following three characteristic parameters can be constructed:

Table 1. Recognition results of different modulated signals

signal	$\|C_{40}\|$	$\|C_{41}\|$	$\|C_{42}\|$	$\|C_{63}\|$	$\|C_{80}\|$
2ASK	$2E^2$	$2E^2$	$2E^2$	$13E^3$	$272E^4$
4ASK	$1.36E^2$	$1.36E^2$	$1.36E^2$	$8.32E^3$	$111.8E^4$
MSK	0	0	E^2	$4E^3$	0
2FSK	0	0	E^2	$4E^3$	0
4FSK	0	0	E^2	$4E^3$	0
BPSK	$2E^2$	$2E^2$	$2E^2$	$13E^3$	$272E^4$
QPSK	E	0	E^2	$4E^3$	$34E^4$
8PSK	0	0	E^2	$4E^3$	E^4
16QAM	$0.68E^2$	0	$0.68E^2$	$2.08E^3$	$13.98E^4$
64QAM	$0.62E^2$	0	$0.62E^2$	$1.80E^3$	$11.50E^4$

(1) Feature parameter Fx_1:

$$Fx_1 = \frac{|C_{41}|}{|C_{42}|} \tag{6}$$

This parameter can divide the signal into {MASK, BPSK} and {MFSK, MPSK, MQAM} sets.

(2) Feature parameter Fx_2:

$$Fx_2 = \frac{|C_{80}|}{|C_{42}|^2} \tag{7}$$

This parameter can divide the signal into {QPSK}, {16QAM, 64QAM} and {MFSK, 8PSK} sets.

(3) Feature parameter Fx_3:

$$Fx_3 = \frac{|C_{63}|^2}{|C_{42}|^3} \tag{8}$$

This parameter can realize intra-class discrimination of MASK signals and intra-class discrimination of MFSK signals.

In this paper, instantaneous information and high-order cumulants are combined to form a 7-dimensional eigenvector, and then the signal is extracted according to these seven feature parameters.

3. CLASSIFIER DESIGN

3.1 Decision tree classifier

Decision tree classifier is the most commonly used classification algorithm in machine learning. A complete decision tree contains one root node, several internal nodes and several leaf nodes [13]. The leaf node corresponds to the decision result. The purpose of decision tree learning is to produce a decision tree with strong adaptability, which is trained as a recursive process. The most important step in the learning process is to select the optimal partition attribute, which can make the node more pure. Common partition methods include information gain, gain rate and Gini index. In this paper, the Gini index is used to measure the purity of each node of the decision tree. The smaller the Gini index is, the higher the purity of the sample will be.

Before using the decision tree classifier, it is necessary to set the relevant parameters of the decision tree, including the maximum number of categories, the depth of the decision tree, the minimum number of samples of nodes, etc. The specific parameters of decision tree classifier in this paper are shown in Table 2.

Table 2. Relevant parameters of decision tree classifier

Parameter name	**Value**
MaxCategories	4
MaxDepth	10

MinSampleCount	5
CVFolds	0
UseSurrogates	False
Use1SERule	False
TruncatePrunedTree	True
RegressionAccuracy	0

3.2 Neural network classifier
Neural network is a network formed by the interconnection of a large number of neurons. Its basic unit is neurons. In the process from input space to output space, the neural network constantly adjusts the weights and thresholds of the network to find the relationship between variables in order to achieve the best classification effect [14]. Because the feature parameters have been extracted before signal recognition, it belongs to modulation recognition based on shallow neural network. In order to be applied in engineering, this paper chooses BP neural network with stable and simple structure. The number of layers of neural network is chosen in three layers, namely input layer, hidden layer and output layer. Through a large number of experiments, the number of hidden layer neurons in this paper is 20. In this paper, the activation function of the neural network is Sigmoid function, and the learning algorithm is RPROP algorithm. In order to improve the accuracy, the maximum training times are set at 10000 times, and the training accuracy is 0.000001.

3.3 Support vector machine classifier
Support Vector Machine (SVM) is a linear binary classification model. Its basic idea is to transform the non-linear problem into a high-dimensional linear separable problem, and then find the optimal linear interface [15]. For linear separable problems, SVM can find the optimal classification hyperplane in the original space; for non-linear separable problems, SVM need to map low-dimensional spatial data into high-dimensional space, and then to find the optimal classification hyperplane. SVM can solve the problem of small sample and non-linearity better. In OpenCV, C_SVC and NU_SVC can realize the function of multi-classification, so they can only be selected when realizing modulation type recognition. C_SVC is called Class C Support Vector Machine (CSVM) classifier, which allows incomplete classification with outlier penalty factor C; NU_SVC is called Class C Support Vector Machine (CSVM). The commonly used kernels in support vector machines are linear kernels, Sigmoid kernels, RBF kernels and INTER kernels. This paper chooses INTER kernels to train data after many experiments.

4. SIMULATION AND ANALYSIS
This paper will use Matlab R2016b, OpenCV310 and Visual Studio 2010 to test the modulation recognition algorithm. The computer environment used in the experiment is Windows 1064-bit operating system, the CPU is Intel Core i5-6300HQ, and the computer memory is 12.0GB.

4.1 Establish classification model
We use MFC and OpenCV310 to construct a classification system of modulation recognition based on machine learning under Visual Studio 2010 platform. The interface of the classification system is shown in Figure 2. The system is divided into three modules: operation area, parameter setting and display area. The system can set the specific parameters of the classifier in detail, and realize the function of classifying and identifying the signals that have been extracted features, including the training of the classifier and the recognition of the signals.

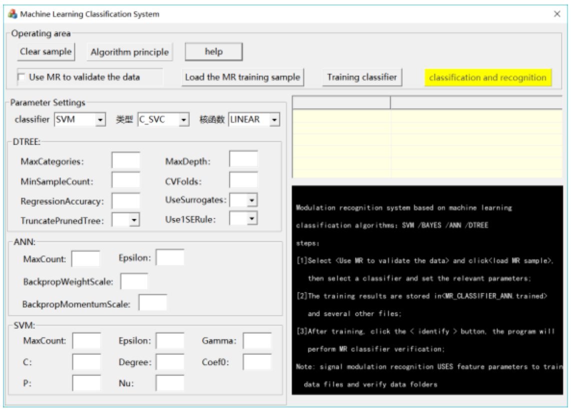

Figure 2. Machine learning classification system.

4.2 Generate experimental data
For the training and validation data used in machine learning, this paper simulates the generation of training and validation data set under the platform of Matlab. The data set contains the following contents:

(1) There are ten kinds of digital modulation signals: 2ASK, 4ASK, MSK, 2FSK, 4FSK, BPSK, QPSK, 8PSK, 16QAM and 64QAM.

(2) The parameters of the simulation signal: carrier frequency is 4000Hz, sampling frequency is 2400Hz, symbol rate is 3000bit/s, symbol number is 1024, noise is Gauss white noise, SNR range of 0~29dB, step length of 1dB.

(3) The ten kinds of digital signals are labeled and numbered according to the sequence of signals in (1) starting from No. 1.

(4) According to the parameter set in the second section, the feature of the simulated signal is extracted, and the 7-dimensional feature vector is obtained by the feature. The set of characteristic parameters in this paper is $\{Ma_1, Ma_2, M_{asm}, Fx_1, Fx_2, Mf_1, Fx_3\}$.

(5) A total of 90,000 sets of feature data were generated by simulation, of which 60,000 were used as training classifiers and 30,000 were used to verify the classification effect.

4.3 Experiment and analysis
In this section, we will use three machine learning classifiers to analyze ten kinds of simulation signals.

4.3.1 The results of using decision tree classifier
Table 3 shows the recognition results using decision tree classifier. The table lists eight SNR recognition cases.

Table 3. Recognition results of different modulated signals

Signal	Recognition rate(%)							
	0dB	3dB	5dB	7dB	10dB	15dB	20dB	25dB
2ASK	100	100	100	100	100	100	100	100
4ASK	100	100	100	100	100	100	100	100
MSK	80	80	90	100	100	100	100	100
2FSK	80	100	100	100	100	100	100	100
4FSK	100	100	100	100	100	100	100	100
BPSK	100	100	100	100	100	100	100	100
QPSK	60	100	100	100	100	100	100	100
8PSK	80	80	95	100	100	100	100	100
16QAM	100	100	100	100	100	100	100	100
64QAM	100	100	100	100	100	100	100	100

From Table 3, it can be seen that the recognition rate of all signals obtained by using decision tree classifier can reach 100% under the SNR of more than 10 dB. Except MSK, 2FSK, QPSK and 8PSK, all the other digital signals can get 100% recognition rate at 0 dB SNR. The recognition rate of MSK, QPSK and 8PSK can still reach 100% under the SNR of more than 5dB. It can be proved that the decision tree classifier in machine learning can automatically find the decision threshold value of the classification boundary through the relationship between the data, which has a better classification effect.

4.3.2 The results of using neural network classifier

Table 4 shows the recognition results using neural network classifiers. The table lists eight SNR recognition cases.

Table 4. Recognition results of different modulated signals

Signal	Recognition rate(%)							
	0dB	3dB	5dB	7dB	10dB	15dB	20dB	25dB
2ASK	100	100	100	100	100	100	100	100
4ASK	100	100	100	100	100	100	100	100
MSK	50	70	90	100	100	100	100	100
2FSK	40	60	100	100	100	100	100	100
4FSK	80	90	100	100	100	100	100	100
BPSK	100	100	100	100	100	100	100	100
QPSK	60	100	100	100	100	100	100	100
8PSK	90	50	90	100	100	100	100	100
16QAM	90	100	100	100	100	100	100	100
64QAM	100	100	100	100	100	100	100	100

As can be seen from Table 4, the recognition rate of all signals increases with the increase of SNR. Except MSK, 2FSK, QPSK, 8PSK and 16QAM, the recognition rate of other signals can reach 100% at the SNR of 0dB.The recognition rate of MSK, 8PSK and QPSK is 100% when the SNR is more than 5dB. From the data in the table, it can be seen that the neural network classifier has better recognition performance and can improve the recognition rate of signals at low SNR.

4.3.3 The results of using support vector machine classifier

Table 5 shows the recognition results using support vector machine classifier. The table lists eight SNR recognition cases.

Table 5. Recognition results of different modulated signals

Signal	Recognition rate(%)							
	0dB	3dB	5dB	7dB	10dB	15dB	20dB	25dB
2ASK	100	100	100	100	100	100	100	100
4ASK	100	100	100	100	100	100	100	100
MSK	70	60	60	100	100	100	100	100
2FSK	20	60	60	80	90	100	100	100
4FSK	80	20	90	100	100	100	100	100
BPSK	100	100	100	100	100	100	100	100
QPSK	50	70	40	60	70	90	80	90
8PSK	50	70	50	50	90	60	80	80
16QAM	100	100	100	100	100	100	100	100
64QAM	100	100	100	100	100	100	100	100

From Table 5-8, it can be found that the recognition results obtained by using support vector machine are inferior to those obtained by decision tree classifier and neural network classifier. For 2ASK, 4ASK, BPSK, 16QAM and 64QAM, the recognition rate can still guarantee 100% at 0dB. The recognition rate of MSK and 4FSK signals can reach 90% above the SNR of 10 dB, but it is not stable enough, and there will be misjudgement under high SNR. The worst recognition results are 2FSK, 8PSK and QPSK signals. The recognition rate of 2FSK signals is very low at low SNR. The recognition rate of QPSK and 8PSK signals is also increasing with the increase of SNR, but can only be maintained at about 80%. It can be seen that when using support vector machine classifier, the extracted feature parameters are not clear enough for the classification boundaries of 8PSK and QPSK signals.

4.3.4 Performance comparison of different classifiers

In this experiment, three kinds of modulation recognition technologies are compared and analyzed. Table 5-10 shows the comparative data of different modulation recognition technologies in different aspects.

Table 6. Recognition results of different modulated signals

Index	Classifier types		
	decision tree	neural network	Support Vector Machine
Identification type	10	10	10
Recognition rate (5dB)	>95%	>95%	>85%
Recognition rate (10dB)	>99%	>99%	>90%
Recognition rate (15dB)	>99%	>99%	>95%
Total recognition rate	98.47%	95.90%	88.23%
Algorithmic complexity	Low	High	High
Simulation time	227.5ms	30882.3ms	17858.0ms

From Table 6, it can be seen that the types of signals recognized by the three modulation recognition methods are the same. Table 6 shows the statistical recognition rates of each modulation recognition mode under three SNR. It can be found that under the same SNR, the recognition rate using support vector machine is the lowest, and the recognition rate using neural network and decision tree classifier is higher. Especially, the recognition rate of modulation recognition technology based on support vector machine is unsatisfactory under various SNR. The main reason is that the distinguishing degree of feature parameters of 2FSK, QPSK and 8PSK is low. In addition, compared with the total recognition rate, algorithm complexity and simulation time, it can be seen that the application of decision tree classifier has the highest total recognition rate, low algorithm complexity, less simulation time, and the overall recognition effect is the best, which is suitable for engineering implementation.

5. CONCLUSIONS

This paper describes a modulation recognition method based on machine learning, which combines instantaneous information features with high-order cumulant features, and realizes modulation recognition of signals by using classification algorithm in machine learning. On the basis of a single feature, this paper combines the advantages of the two feature types to improve the signal discrimination under low SNR. In addition, the three different machine learning classification algorithms used in this paper can analyze the relationship between parameters adaptively, and better solve the problem of recognition under low SNR. Experimental results show that the method in this paper is simple, computational complexity is small, recognition rate is high, recognition types are many, and can be better applied in engineering.

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